

A Control Theory for Stochastic Biomolecular Regulation

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CONTROL THEORY & SYSTEMS BIOLOGY



Introduction



Reaction networks

A reaction network is...

- A set of d distinct species X_1, \dots, X_d
- A set of K reactions R_1, \dots, R_K specifying how species interact with each other and for each reaction we have
 - A stoichiometric vector $\zeta_k \in \mathbb{Z}^d$ describing how reactions change the state value
 - A propensity function $\lambda_k \in \mathbb{R}_{\geq 0}$ describing the "strength" of the reaction



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Deterministic networks

- Large populations (concentrations are well-defined), e.g. as in chemistry
- Lots of analytical tools, e.g. reaction network theory, dynamical systems theory, Lyapunov theory of stability, nonlinear control theory, etc.



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Stochastic networks

- Low populations (concentrations are NOT well defined)
- Biological processes where key molecules are in low copy number (mRNA $\simeq 10$ copies per cell)
- No well-established theory for biology, "analysis" often based on simulations. . .
- No well-established control theory



Chemical master equation

State and dynamics

- The state $X \in \mathbb{N}_0^d$ is vector of random variables representing molecules count
- The dynamics of the process is described by a jump Markov process $(X(t))_{t \geq 0}$



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Chemical Master Equation (Forward Kolmogorov equation)

$$\dot{p}_{x_0}(x, t) = \sum_{k=1}^K \lambda_k(x - \zeta_k) p_{x_0}(x - \zeta_k, t) - \lambda_k(x) p_{x_0}(x, t), \quad x \in \mathbb{N}_0^d$$

where $p_{x_0}(x, t) = \mathbb{P}[X(t) = x | X(0) = x_0]$ and $p_{x_0}(x, 0) = \delta_{x_0}(x)$.

Solving the CME

- Infinite countable number of linear time-invariant ODEs
- Exactly solvable only in very simple cases
- Some numerical schemes are available (FSP, QTT, etc) but limited by the curse of dimensionality; if $X \in \{0, \dots, \bar{x} - 1\}^d$, then we have \bar{x}^d states



Ergodicity of reaction networks

Ergodicity

A given stochastic reaction network is **ergodic** if there is a probability distribution π such that for all $x_0 \in \mathbb{N}_0^d$, we have that $p_{x_0}(x, t) \rightarrow \pi$ as $t \rightarrow \infty$.





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Theorem (Condition for ergodicity¹)

Assume that

- (a) *the state-space of the network is irreducible; and*
- (b) *there exists a norm-like function $V(x)$ such that the **drift condition***

$$\sum_{i=1}^K \lambda_i(x) [V(x + \zeta_i) - V(x)] \leq c_1 - c_2 V(x)$$

holds for some $c_1, c_2 > 0$ and for all $x \in \mathbb{N}_0^d$. Then, the stochastic reaction network is ergodic.

¹ S. P. Meyn and R. L. Tweedie. Stability of Markovian processes III: Foster-Lyapunov criteria for continuous-time processes, *Adv. Appl. Prob.*, 1993





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Choosing $V(x) = \langle v, x \rangle$, $v > 0$, allows to establish the ergodicity of a wide class of existing reaction networks²

¹ S. P. Meyn and R. L. Tweedie. Stability of Markovian processes III: Foster-Lyapunov criteria for continuous-time processes, *Adv. Appl. Prob.*, 1993

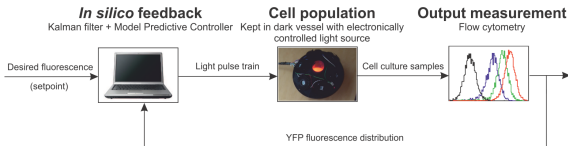
² A. Gupta, C. Briat, and M. Khammash. A scalable computational framework for establishing long-term behavior of stochastic reaction networks, *PLOS Computational Biology*, 2014



Control problems

In-silico control

- Controllers are implemented outside cells
- Single cell¹ or population control²



¹ J. Uhlenendorf, et al. Long-term model predictive control of gene expression at the population and single-cell levels, *Proceedings of the National Academy of Sciences of the United States of America*, 2012

² A. Miliadis-Argeitis, et al. In silico feedback for in vivo regulation of a gene expression circuit, *Nature Biotechnology*, 2011

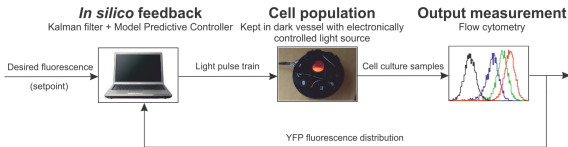




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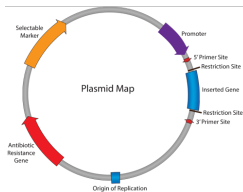
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In-vivo control

- Controllers are implemented inside cells
- Single cell and population control³



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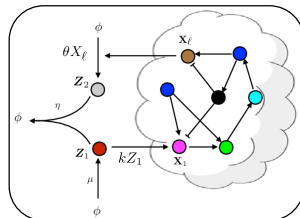
³ C. Briat, A. Gupta, and M. Khammash. Integral feedback generically achieves perfect adaptation in stochastic biochemical networks, *ArXiv*, 2015

In-vivo population control - Theory



Open-loop reaction network

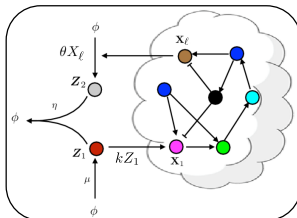
- d molecular species: X_1, \dots, X_d
- X_1 is the actuated species: $\emptyset \xrightarrow{u} X_1$
- Measured/controlled species: $Y = X_\ell$





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Problem

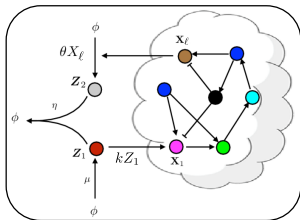
Find a controller such that the closed-loop network is ergodic and such that we have

$$\mathbb{E}[Y(t)] \rightarrow \mu \text{ as } t \rightarrow \infty, \text{ for some reference value } \mu$$



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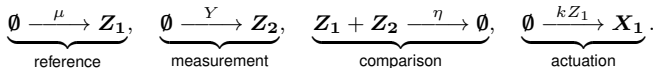


Problem

Find a controller such that the closed-loop network is ergodic and such that we have $\mathbb{E}[Y(t)] \rightarrow \mu$ as $t \rightarrow \infty$, for some reference value μ

The controller

- Two species Z_1 and Z_2 .



where $k, \eta > 0$ are control parameters.



The hidden integral action¹

Moments equations

$$\frac{d}{dt}\mathbb{E}[Z_1(t)] = \mu - \eta\mathbb{E}[Z_1(t)Z_2(t)]$$

$$\frac{d}{dt}\mathbb{E}[Z_2(t)] = \mathbb{E}[Y(t)] - \eta\mathbb{E}[Z_1(t)Z_2(t)].$$

¹ K. Oishi and E. Klavins. Biomolecular implementation of linear I/O systems, *IET Systems Biology*, 2010



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Integral action

- We have that

$$\frac{d}{dt}\mathbb{E}[Z_1(t) - Z_2(t)] = \mu - \mathbb{E}[Y(t)],$$

so we have an integral action on the mean

- Closed-loop ergodic $\Rightarrow \mathbb{E}[Y(t)] \rightarrow \mu$ as $t \rightarrow \infty$
- No need for solving moments equations \rightarrow **no closure problem :**

¹  K. Oishi and E. Klavins. Biomolecular implementation of linear I/O systems, *IET Systems Biology*, 2010



General stabilization result

Theorem

Let $V(x) = \langle v, x \rangle$ with $v \in \mathbb{R}_{>0}^d$ and $W(x) = \langle w, x \rangle$ with $w \in \mathbb{R}_{\geq 0}^d$, $w_1, w_\ell > 0$.

Assume that

- (a) the state-space of the open-loop reaction network is irreducible; and
- (b) there exist $c_1, c_3 > 0$ and $c_2 \geq 0$ such that

$$\begin{aligned} \sum_{k=1}^K \lambda_k(x) [V(x + \zeta_k) - V(x)] &\leq -c_1 V(x), \\ \sum_{k=1}^K \lambda_k(x) [W(x + \zeta_k) - W(x)] &\geq -c_2 - c_3 x_\ell, \end{aligned} \tag{1}$$

hold for all $x \in \mathbb{N}_0^d$ (together with some other technical conditions).

Then, the closed-loop network is ergodic and we have that $\mathbb{E}[Y(t)] \rightarrow \mu$ as $t \rightarrow \infty$.



Unimolecular networks

Theorem

Let us consider a unimolecular reaction network with irreducible state-space. Assume that its first-order moments system

$$\begin{aligned} \frac{d}{dt} \mathbb{E}[X(t)] &= A \mathbb{E}[X(t)] + e_1 u(t) \\ y(t) &= e_\ell^T \mathbb{E}[X(t)] \end{aligned} \quad (2)$$

is



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is

- (a) asymptotically stable, i.e. A Hurwitz stable (LP)
- (b) output controllable, i.e. $\text{rank} \begin{bmatrix} e_\ell^T e_1 & e_\ell^T A e_1 & \dots & e_\ell^T A^{d-1} e_1 \end{bmatrix} = 1$ (LP)



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Then, for all control parameters $k, \eta > 0$,

- (a) the closed-loop reaction network (system + controller) is ergodic
- (b) all the first and second order moments of the random variables X_1, \dots, X_d are uniformly bounded and globally converging
- (c) $\mathbb{E}[Y(t)] \rightarrow \mu$ as $t \rightarrow \infty$.



Closed-loop system

- Robust ergodicity, tracking and disturbance rejection
- Population control is achieved

Controller

- Innocuous: open-loop ergodic & output controllable \Rightarrow closed-loop ergodic
- Decentralized: use only local information (single-cell control)
- Implementable: small number of reactions

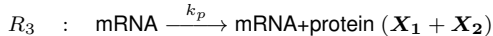
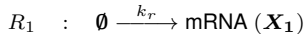
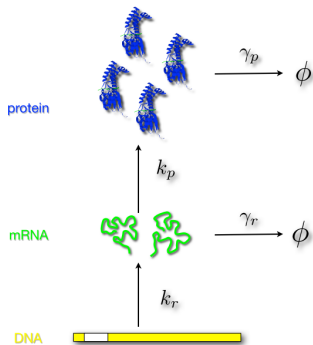
Additional remarks

- No moment closure problem
- Expected to work on a wide class of networks (even though the theory is not there yet)

In-vivo population control - Example



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Department of Biosystems
Science and EngineeringGene expression network $d = 2, K = 4$ 

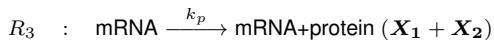
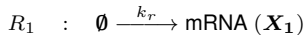
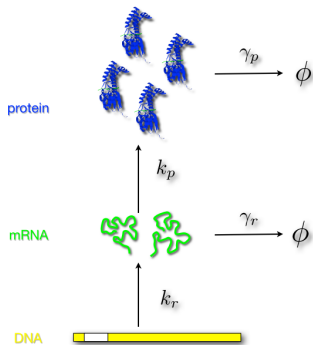
$$S = \begin{bmatrix} \zeta_1 & \zeta_2 & \zeta_3 & \zeta_4 \\ 1 & -1 & 0 & 0 \\ 0 & 0 & 1 & -1 \end{bmatrix}$$

$$\lambda(x) = \begin{bmatrix} \lambda_1(x) & \lambda_2(x) & \lambda_3(x) & \lambda_4(x) \end{bmatrix}^T$$

$$= \begin{bmatrix} k_r & \gamma_r x_1 & k_p x_1 & \gamma_p x_2 \end{bmatrix}^T$$



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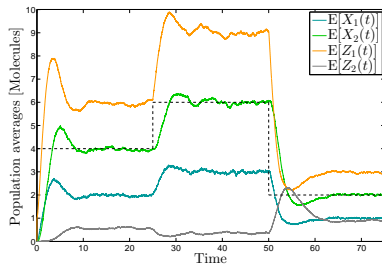
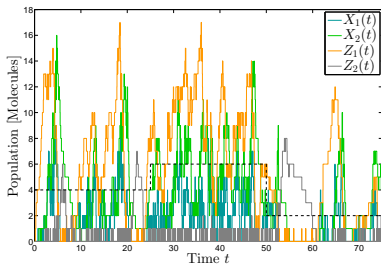
We want to control the average number of proteins by suitably acting on the transcription rate k_r



Gene expression control

Theorem

For any values of the system parameters $k_p, \gamma_r, \gamma_p > 0$ and the control parameters $\mu, k, \eta > 0$, the closed-loop network is ergodic and we have that $\mathbb{E}[X_2(t)] \rightarrow \mu$ as $t \rightarrow \infty$ globally.

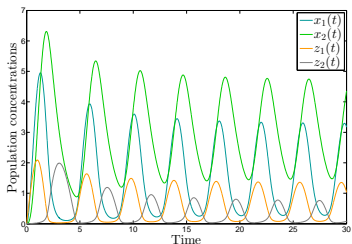




Comparison with deterministic control

Deterministic

$$\begin{aligned}\dot{x}_1 &= kz_1 - \gamma_r x_1 \\ \dot{x}_2 &= k_p x_1 - \gamma_p x_2 \\ \dot{z}_1 &= \mu - \eta z_1 z_2 \\ \dot{z}_2 &= x_2 - \eta z_1 z_2\end{aligned}$$





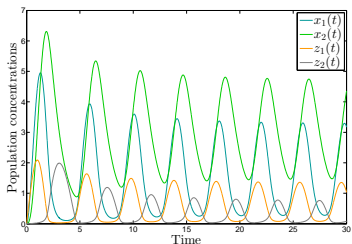
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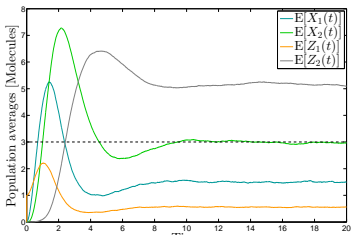
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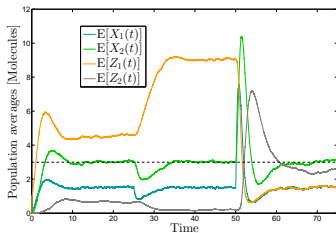
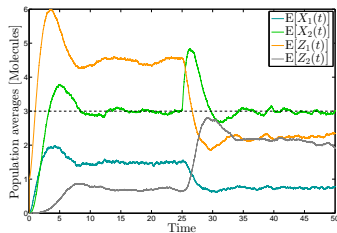
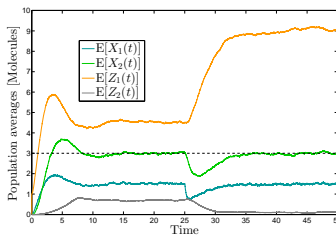
Stochastic

$$\begin{aligned}\dot{\mathbb{E}}[X_1] &= k\mathbb{E}[Z_1] - \gamma_r \mathbb{E}[X_1] \\ \dot{\mathbb{E}}[X_2] &= k_p \mathbb{E}[X_1] - \gamma_p \mathbb{E}[X_2] \\ \dot{\mathbb{E}}[Z_1] &= \mu - \eta \mathbb{E}[Z_1] \mathbb{E}[Z_2] \\ &\quad - \eta V(Z_1, Z_2) \\ \dot{\mathbb{E}}[Z_2] &= \mathbb{E}[X_2] - \eta \mathbb{E}[Z_1] \mathbb{E}[Z_2] \\ &\quad - \eta V(Z_1, Z_2)\end{aligned}$$

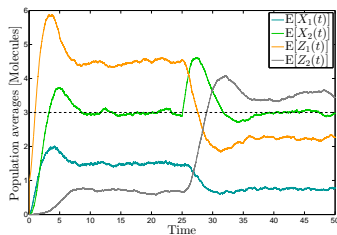




Robustness - Perfect adaptation

(a) Perturbation of the controller gain k (b) Perturbation of the translation rate k_p 

(c) Perturbation of the mRNA degradation rate



(d) Perturbation of the protein degradation rate

Concluding statements



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What has been done

- In-vivo (integral) control motif seems promising
- Population control
- Perfect adaptation



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What needs to be done

- Implementation
- Extensions: bimolecular networks, different inputs, multiple inputs/outputs, different control motifs → biomolecular control theory



Thank you for your attention



Computational results

Theorem

The following statements are equivalent:

- (a) *The matrix A is Hurwitz and the triplet (A, e_1, e_ℓ^T) is output-controllable.*
- (b) *There exist $v \in \mathbb{R}_{>0}^d$ and $w \in \mathbb{R}_{\geq 0}^d$ with $w^T e_1 > 0$, $w^T e_\ell > 0$, such that*

$$v^T A < 0 \quad \text{and} \quad w^T A + e_\ell^T = 0.$$



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$$v^T A < 0 \quad \text{and} \quad w^T A + e_\ell^T = 0.$$

Comments

- Linear program
- Can be robustified \rightarrow if $A \in [A^-, A^+]$, then $v_+^T A^+ < 0$ and $w_-^T A^- + e_\ell^T = 0$.
- Can be made structural $\rightarrow A \in \{\ominus, 0, \oplus\}^{d \times d}$



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Implementation

